**Literature Review**

“Public opinion on climate change is multidimensional, dynamic, and differentiated” (Shwom et al., 2015, p. 269). Climate change opinion is one of the major issues that is continuing to grow in intensity and complexity.

**Data and Method**

**Research Questions**

**Methodology**

The research, as already explained, is mainly composed of two different parts: the first, that uses unsupervised learning to obtain clusters of citizens’ attitudes towards climate change, and the second, that uses supervised learning to predict pro-environment behaviour.

The first set of methods focuses on identifying some profiles of citizens’ attitudes towards climate change using different types of unsupervised learning techniques: K-means clustering and Correlational Class Analysis (CCA).

K-means clustering is a “numerical, unsupervised, non-deterministic, iterative method” (Na et al., 2010, p.63) and it seeks to identify a finite set of clusters or subgroups to describe data (Fonseca, 2013; James et al., 2013). This method creates some subgroups in order to maximize both the similarity within clusters and the differences among other groups.

Correlational Class Analysis (CCA) identify such “cultural schemas” in a survey data, in particular in a public opinion data (Boutyline, 2017; Rossoni et al., 2020). This technique is an implementation of Relational Class Analysis (RCA) developed by Goldberg (2011) and it “seeks to parse out groups, or classes, of like-minded individuals. Unlike these methods, however, it uses relationality to compare these individuals not on their attitudes per se but on the patterns of relations between their attitudes” (p.1399). Therefore, the goal of RCA is to partition individuals into groups which shared “cultural classes” (Rossoni et al., 2020).The shared “cultural schemas” “does not imply having identical attitudes or behaviours, rather it suggests being in agreement on the structures of relevance and opposition that make actions and symbols meaningful” (Goldberg, 2011, p.1402). Therefore, it tries to find patters of associations between attitudes or behaviours in terms of “relationality”. In addition, it tries to find relationships both between individuals and between variables, combining clustering analysis and multidimensional scaling or factor analysis (Goldberg, 2011). The difference between RCA and CCA lies in the concept of “relationality”. In fact, while Goldberg (2011) uses linear dependency between two individuals vectors of responses in order to find the shared cultural schemas, CCA suggests to adopt Pearson’s correlation (Boutyline, 2017). Boutyline (2017) demonstrated that CCA produces more accurate results.

Using these algorithms only quantitative variables can be used, in fact only climate change questions are considered, except for the dependent variable, pro-environmental action, and climate change risk perception.[[1]](#footnote-1) According to scholars it is possible to use Likert scale ordinal data as continuous (Norman, 2010; Sullivan & Artino, 2013). In fact, five questions are selected to fit these methods. The responses were on 4-point scale, with the following gradations and labels (the latter change according to the questions):

1 = Totally agree/ Very important

2 = Tend to agree/ Fairly important

3 = Tend to disagree/ Not very important

4 = Totally disagree/ Not at all important

We assume that the distance that the distance between 1 = “Totally agree” and 2 = “Tend to agree” is the same as 3 = “Not very important” and 4= “Tot at all important”. In addition, neutral/null answers (don’t know) are dropped from the analysis in order to guarantee the distance across categories.

The purpose of this part of analysis is to find some different types of citizens, called clusters or classes, that better describe the data used. In fact, through these techniques some new segmentations of citizens could be identified and then they could help to find new explanations to the phenomenon studied. Theoretically, using these two different types of segmentations of citizens, the results should be opposite. On the one side, the traditional clustering profiles the data according to similar attitudes. On the other side, CCA finds shared cultural schemas, structure of thought. Eventually, the classes obtained from k-means clustering and correlational class analysis are used as predictors in the subsequent classifications.

The second set of methods focuses on prediction climate change pro-environment using different types of supervised learning techniques and classifiers. In fact, classification is used when a categorical variable is predicted (James et al., 2013). “The methods used for classification first predict the probability of each of the categories of a qualitative variable” (James et al., 2013, p. 127).

The different techniques of classifiers are briefly presented as follow.

The action prediction starts with a Logistic Regression. It is a form of binary regression and it explains relationships between a categorical outcome and some continuous or discrete predictors (Peng et al., 2002). It models the probability of being to a particular category (Peng et al., 2002; Stoltzfus, 2011).

The model requires some assumptions:

1. independence of errors;
2. linearity in the logit for continuous independent variables;
3. the absence of multicollinearity among explanatory variables;
4. the absence of extreme outliers

(Stoltzfus, 2011)

However, some assumptions are violated. In fact, there is no present linearity in the logit for age variable. In addition, some outliers are found in climate change risk perception, but they are not so far away from the rest of the value.

In spite of the robustness of the logistic regression models, data cannot fully satisfy the assumptions, also decision tree models are fitted. Decision Tree is a “flow-chart-like hierarchical tree structure” (Jenhani et al., 2008, p. 786) and it is composed of three elements: nodes, edges and leaves. Nodes represent attributes or variables, edges correspond to the different possible attribute values and lastly leaves include objects that typically belong to the same class or that are very similar (Jenhani et al., 2008). The main advantages of decision tree are that it has not assumptions and especially it produces graphical representation, which make it easier to read and to interpret the model.

The analysis continues with another robust model: Random Forest, which is produces of multiple and randomized decision trees that operate as an ensemble (Belgiu, 2016; Biau & Scornet, 2016). This classifier “can successfully handle high data dimensionality and multicollinearity, being both fast and insensitive to overfitting” (Belgiu, 2016, p.24). Another advantage is that it can dealing with unbalanced data, as in this case (Belgiu, 2016).

The last classifier used is Gradient Boosting. It is similar to random forest algorithm, but this case each new tree is been created using the previous ones, in order to correct mistakes made (James et al., 2013). Instead of fitting a large amount of trees separately, it learns slowly by previous trees recursively.

The last two tree-based methods, producing multiple trees, have become more popular since they improve in prediction accuracy but they loss in interpretation (Belgiu, 2016; James et al., 2013).

To sum up, all these classifiers have the possibility to predict pro-environmental behaviour. In the figure 1, you can see the distribution, unbalanced, of the observations according to the dependent variable. We have 14327 individuals who declared to have taken any action to fight climate change over the past six months and 7651 who have not.

Figure 1: Pro-environmental behavior distribution

Socio-demographic variables, classes created form k-means and CCA and climate change risk perception are used as predictors. In fact, we want also to investigate the main factors and predictors that influence pro-environmental behavior. This process is achieved thanks to selected models, logistic regression and tree-based methods, which can determine the importance of independent variables. This part is considered quite conventional according to the literature review, above-mentioned: variables selected have already been used previously, even if have mostly used more traditional techniques (and not machine learning techniques). Instead, the originality of this research can be found in next step. Due to the relevance of climate change risk perception in the pro-environmental behaviour’s prediction, two different analysis, according to the degree of this main explanatory variable, are performed. Two datasets are created: one with only the observations of individuals who declared very worried about the phenomenon (responses with a score greater than or equal to 6 are considered), and one with those who do not care (score less than or equal to 5). The same techniques are fitted for the two different subsets. The aim is to discover the divergent variables that predict actions and whether there are relevant differences between those who care and those who do not care.



Figure 2: Pro-environmental behavior distribution according to Climate Change Risk Perception

The figure 2 indicates the distribution of our dependent variable according to the 2 created subsets. The subset with the observations of those who warried is definitely greater: 12988 observations of those who have not done any ecological behaviour and 6084 individuals who have done nothing. Instead, the second dataset is composed by the observations those who do not care about environment. We have few cases, but they are balanced: 1339 and 1567, respectively who does environmentally behaviours and who does not.

**Data Description**

As aforementioned, the research studies pro-environmental behaviour of European citizens. The main data used in this project come from one wave of Eurobarometer survey. The Eurobarometer is a public opinion research institution in the European Union with the aim to examine a variety of topics and attitudes. The European Commission conducts Standard & Special Eurobarometer periodically. We used the Special Eurobarometer 91.3 dataset, entitled “Climate Change”, made available by the Eurobarometer Open Data website. This survey is collected in April 2019 using face-to-face interviews. There are 27655 respondents from 28 countries of the European Union. The Eurobarometer data are publicly available from GESIS (European Commission, Brussels, 2019). Eurobarometer 91.3 asks some questions about environmental issues and some socio-demographic information. Some relevant items about climate change and socio-demographic variables are selected.[[2]](#footnote-2)

**Data Cleaning**

The first step before performing the analysis is data cleaning. In order to obtain an accurate analysis some observations are dropped. In fact, missing data or refusal answers of climate change issues are not considered in the final dataset. The missing data of our dependent variables, pro-environmental behavior (encoded as qb5), is dropped since the analysis is based on the predictions of a dichotomous outcomes (coded as 1 = Yes, 0= No). Climate change risk perception (qb2) is measured on 1-10 scale, and no answers are dropped to keep the variables as a metric. The question does not directly about the perceived risk but it is referred of *seriousness* of the phenomenon in the present moment and it is a one-dimension of climate change risk perception (Echavarren et al., 2019). Successively, other questions regarding the topic are selected, all expressed on a 4-point Likert scale, as already mentioned above. Also, in this case, missing or refusal data is removed. The reason why k-means clustering and CCA does not accept missing data and therefore the entire observation must be removed. Instead, socio-demographic variables are for the most part categorical and therefore *refusal* or *dk* (don’t know) are kept among the answer choices. However, some transformations are adopted in these variables. Political orientation (d1) is originally presented in a 10-points Likert scale (1 = left to 10 =right). It is transformed into a categorical variable: the answers 1-2 are become “left”, 3-4 “centre-left”, 5-6 “centre”, 7-8 “centre-right”, 9-10 “right” and *dk* or *refusal* “not positionable”. For the current situation variable (d7), some new categories are created depending on whether individual has declared that he/she lives with “partner”, “partner and children” or he/she is “single” or “single (and he/she lives) with children”. The education variable (d8), or rather when he/she finished studying, is been converted from continuous to categorical. According to scholars (Abu-Omar & Rütten, 2008; Loyen, 2016) five categories are created: “up to 15 years”, “16-19 years”, “20+years”, “still studying” and “refusal/other”. Gender (d10) and age (d11) are not manipulated since nobody answered with “other” and therefore the first variable is a dichotomous “male” and “female” option, while the second one is maintained as continuous. For place of residence (d25) and class identity (d63) variables, the categories proposed by the Eurobarometer are kept. Respectively, the first has the following classes: “rural area or village”, “small or middle sized town”, “large town” and “dk” (don’t know). While the second one has the options: “the working class of society”, “the lower middle class of society”, “the middle class of society”, “the upper middle class of society”, “the higher class of society”.[[3]](#footnote-3)

Lastly, country variable is considered. Eurobarometer surveys collected about 1000 interviews on the average for each country, except for small nations, such as Malta and Luxembourg. Only a manipulation is computed: West and East Germany are combined into one country “Germany”.

To sum up, the final dataset has 21978 respondents (out of 27655).[[4]](#footnote-4)

**Analysis**

The following section illustrates the different steps undertaken to obtain a prediction model for pro-environmental action. In particular, the first step consists of Exploratory Data Analysis, in order to investigate climate change attitudes. Then, the best fitting models tested to predict the final price are presented.

**Exploratory Data Analysis**

Climate change attitudes do not vary only between countries but also between citizens in the same country (Xie et al., 2019). As you can see in the figure 1, the percentage of those who believe that climate change is the single most serious problem varies significantly according to country. For example, Bulgaria and Croatia obtain the smaller percentage, that is 11% of citizens who think climate change is the single most serious problem. On the contrary, about 1 out 2 Sweden’s citizen indicated climate change.



Figure 1: Single Most Serious Problem

Another interesting example is the difference in the climate change risk perception. As you can see in the figure 2, about half of citizens of Malta and Luxemburg declared that they are extremely worrying about the phenomenon studied.



Figure 2: Climate Change Risk Perception

Attitudes among countries could be so vary since they are influenced by different contextual factors (Echavarren et al., 2019; Krajhanzl, 2010). According to Echavarren and colleagues (2019), opinion, perception and behavior could change due to different natural hazards and political context. For example water deficit or temperature growth regarding natural hazards and the “level of environmentalism in the political arena of a given country” (Echavarren et al., 2019, p. 815) for political variables. These macro-variables should be significant mediators in explaining risk perception or pro-environmental behaviour. Some indexes are considered with the sole purpose of remembering that they could affect and moderate the phenomenon studied. Then, they are not inserted in the final models since only multilevel method could be adopted. In addition, the aim of the research is not to evidence national or cultural differences, but on the contrary, it is to find patterns at individual levels, regardless of the place of origin. However, these differences at the macro levels are presented.

For the natural hazards the 2020 Environmental Performance Index (EPI) is used (the 2019 EPI is not available in order to use the same data of year of the survey) (Yale Center for Environmental Law & Policy, 2020). EPI quantifies numerically environmental health and ecosystem vitality around the world. Some indicators that composed the index are: air pollution, drinking water quality, species protection. These phenomena could be positively affect climate change concerns and opinion (Echavarren et al., 2019). In fact, citizens should perceive biodiversity loss or temperature increases, leading to greater apprehension. The figure 3 shows the score across European Union (EU). The best score is obtained from Denmark, while the worst from Bulgaria.

Figure 3: The 2020 EPI

For the political context the 2019 Climate Change Policy Performance is selected, which is a mesarument of national and international climate policies (Burck, 2018) developed by organisation Germanwatch. It is one of the indicators that belongs to the Climate Change Performance Index (CCPI). The indicator constitutes the measurements taken by governments in order to reduce current level of GHG emissions per capita or the use of renewavle energy. Briefly it is defined as a measure of countries’ progress and their capacity to climate protection (Burck, 2018). In the Climate Change Policy the record goes to Portugal and Bulgaria gets the lowest score in all European Union, as the figure 4 shows.

According to scholars (Echavarren et al., 2019; van der Linden, 2015) socio-cultural context influces individual attitudes towards climate change concerns. Therefore, the notable diferencess in attitudes across coutries should be also due to these indicators. In fact, “sociological research suggests that contextual factors and processes can be powerful forces shaping how individuals and communities engage with the issue” (Lee et al., 2015, p. 1014). There are different ecological tax reforms or cultural habits that affect and shape individual climate change attitudes and behavior.

In this way, It is important to remember that these macro-factors should have an effect also in individual preferences.

Figure 4: The 2019 Climate Change Policy

**APPENDIX**

**APPENDIX A. Survey Question Wording and Coding**

|  |  |  |
| --- | --- | --- |
| **Variables** | **Questions** | **Coding** |
|  | ***Question about Climate Change issues*** |  |
| qb2 | And how serious a problem do you think climate change is at this moment? Please use a scale from 1 to 10, with '1' meaning it is "not at all a serious problem" and '10' meaning it is "an extremely serious problem" | 1-10 scale: 1= Not at all a serious problem to 10= An extremely serious problem |
| qb4\_3 | To what extent do you agree or disagree with each of the following statements? Taking action on climate change will lead to innovation that will make EU companies more competitive | 1-4 scale: 1= Totally agree to 4 = Totally disagree |
| qb4\_5 | To what extent do you agree or disagree with each of the following statements? Adapting to the adverse impacts of climate change can have positive outcomes for citizens in the EU | 1-4 scale: 1= Totally agree to 4 = Totally disagree |
| qb5 | Have you personally taken any action to fight climate change over the past six months? | 1= Yes; 0= No |
| qb7 | How important do you think it is that the (NATIONALITY) government sets ambitious targets to increase the amount of renewable energy used, such as wind or solar power, by 2030? | 1-4 scale: 1= Very important to 4= Not at all important |
| qb8 | How important do you think it is that the (NATIONALITY) government provides support for improving energy efficiency by 2030 (e.g. by encouraging people to insulate their home or buy electric cars)? | 1-4 scale: 1= Very important to 4= Not at all important |
| qb9 | To what extent do you agree or disagree with the following statement: We should reduce greenhouse gas emissions to a minimum while offsetting the remaining emissions, for instance by increasing forested areas, to make the EU economy climate neutral by 2050. | 1-4 scale: 1= Very important to 4= Not at all important |
|  | ***Socio-demographic information*** |  |
| d1 | In political matters people talk of "the left" and "the right". How would you place your views on this scale? | 1-10 scale: 1= left to 10= Right |
| d7 | Which of the following best corresponds to your own current situation? | Categorical |
| d8 | How old were you when you stopped full-time education? | Number in actual years |
| d10 | Gender | Female; Male |
| d11 | How old are you? | Number in actual years |
| d25 | Would you say you live in a...? | Categorical |
| d63 | Do you see yourself and your household belonging to…? | Categorical |
| country | Country | Categorical |

**APPENDIX B. Summary Statistics.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Obs.** | **Mean** | **Std. Dev.** | **Min** | **Max** |
| **Qb5** | 21978 |  |  |  |  |
| *Yes* | *14327* |  |  |  |  |
| *No* | *7651* |  |  |  |  |
| **Qb2** | 21978 | 7.93 | 2.02 | 1 | 10 |
| **Qb4\_3** | 21978 | 1.74 | 0.71 | 1 | 4 |
| **Qb4\_5** | 21978 | 1.90 | 0.87 | 1 | 4 |
| **Qb7** | 21978 | 1.52 | 0.65 | 1 | 4 |
| **Qb8** | 21978 | 1.56 | 0.68 | 1 | 4 |
| **Qb9** | 21978 | 1.50 | 0.62 | 1 | 4 |
| **D1** | 21978 |  |  |  |  |
| *Left* | *1853* |  |  |  |  |
| *Centre-letf* | *3856* |  |  |  |  |
| *Centre* | *7968* |  |  |  |  |
| *Centre-right* | *3470* |  |  |  |  |
| *Right* | *1603* |  |  |  |  |
| *Not positionable* | *3228* |  |  |  |  |
| **D7** | 21978 |  |  |  |  |
| *Partner* | *7791* |  |  |  |  |
| *Patner and children* | *7000* |  |  |  |  |
| *Single* | *5975* |  |  |  |  |
| *Single with children* | *1120* |  |  |  |  |
| *Refusal/Other* | *92* |  |  |  |  |
| **D8** | 21978 |  |  |  |  |
| *Up to 15 years old* | *2665* |  |  |  |  |
| *16-19 years old* | *10013* |  |  |  |  |
| *20+ years old* | *8981* |  |  |  |  |
| *Refusal/dk* | *319* |  |  |  |  |
| **D10** | 21978 |  |  |  |  |
| *Man* | *10527* |  |  |  |  |
| *Woman* | *11451* |  |  |  |  |
| **D11** | 21978 | 50.51 | 17.88 | 15 | 98 |
| **D25** | 21978 |  |  |  |  |
| *Rural area or village* | *7068* |  |  |  |  |
| *Small or middle sized town* | *8510* |  |  |  |  |
| *Large town* | *6396* |  |  |  |  |
| *Dk* | *4* |  |  |  |  |
| **D63** | 21978 |  |  |  |  |
| *The higher class of society* | *154* |  |  |  |  |
| *The lower middle class of society* | *3456* |  |  |  |  |
| *The middle class of society* | *10942* |  |  |  |  |
| *The upper middle class of society* | *1630* |  |  |  |  |
| *The working class of society* | *5276* |  |  |  |  |
| *Refusal/Other* | *520* |  |  |  |  |

**APPENDIX C. Sample composition**

|  |  |
| --- | --- |
| **Country** | **Obs.** |
| Austria | 830 |
| Belgium | 970 |
| Bulgaria | 626 |
| Croatia | 904 |
| Cyprus | 411 |
| Czech Republic | 729 |
| Denmark | 839 |
| Estonia | 520 |
| Finland | 807 |
| France | 797 |
| Germany | 1200 |
| Greece | 854 |
| Hungary | 900 |
| Ireland | 928 |
| Italy | 905 |
| Latvia | 687 |
| Lithuania | 704 |
| Luxembourg | 399 |
| Malta | 397 |
| Netherlands | 883 |
| Poland | 710 |
| Portugal | 863 |
| Romania | 869 |
| Slovakia | 810 |
| Slovenia | 874 |
| Spain | 820 |
| Sweden | 890 |
| United Kingdom | 852 |
| **Total** | **21978** |

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1. See table 1 for the list of variables. [↑](#footnote-ref-1)
2. See Appendix A for the list of variables. [↑](#footnote-ref-2)
3. See Appendix B for the summary statistics. [↑](#footnote-ref-3)
4. See Appendix C for the number of observations according to country. [↑](#footnote-ref-4)